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The Effect of BDAC on Supply Chain Innovation: The Mediating Role of Learning Orientation

By

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DECLARATION

I hereby declare that this submission is my work towards the Masters of Science in Logistics and Supply Chain Management and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

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DEDICATION

I dedicate this project work to the Almighty God for granting me the blessings that I needed to successfully complete this project and making this study a success. I would also like to dedicate this to my husband, Dr. Emmanuel Donkor, my mum Mrs. Joyce Affum, my siblings and the entire family for the support granted me. I say may God bless you all. I am very grateful for all the unflinching love and directions you gave me.

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ABSTRACT

The study was conducted to examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. A descriptive and explanatory research designs was employed for this study's data collection. A quantitative method was used for this investigation. The 264 procurement, logistics, and top executives or managers were chosen using a stratified sampling process. The major method of collecting information was a predetermined questionnaire. Statistical analysis was performed using both SPSS v26 and SmartPls v4. The data was analysed using both descriptive and inferential methods. The finding reveals a significant positive direct influence on BDAC to SCI and LO. BDAC had a significant positive direct influence on LO. Lastly, LO positively mediates BDAC-SCI interactions. When senior management values research and development, technical leadership, and innovations, SC innovation improves. It encourages all workers to think creatively about supply chain operations, service delivery, and technology. The research advocated emphasising staff development and encouraging creative behaviour to attain competitive advantage and company sustainability.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

A combination of phenomena such as increasing adoption of supply chain technology, use of data and shifting focus from heuristics to data-driven decision-making has resulted in a massive data boom (Dubey et al., 2019). As a component of decision-making, Big Data Analytics Capability (BDAC) can play an important role in transforming and improving supply chain innovation (Shokouhyar et al., 2020). In this ever-changing business environment, business leaders prefer to make decisions based on data rather than relying on their intuition (Mikalef et al., 2019). Given the perceived benefits of BDAC, organizations are strongly encouraged to develop their technical and organizational capabilities to extract value from data (Bahrami et al., 2022). However, practitioners face significant challenges in understanding the skills required to transform data into value (AlNuaimi et al., 2021).

The main aspect of production quality relies on the organization's ability to retrieve, store and analyze large amounts of complex data in real time or near real time through the development of analytical support (Lee and Mangalaraj, 2022). Although the 'Big Data' phenomenon is considered to be the newest phenomenon in the world, it actually appears out of nowhere (Awan et al., 2021). Over the past decade, the use of various forms of Information and Communication Technology (ICT) for Supply Chain Management (SCM) has increased dramatically (Chen et al., 2019; Luthra et al., 2018; Singh el al., 2019), Enterprise Resource Planning (ERP) and Internet of Things (IoT) (Tavana et al., 2020; Lee et al., 2018; Jirasatjanukul et al., 2019). This results in massive data generation in the supply chain (Fosso Wambabet al., 2018). Our continuous efforts to develop advanced technologies for data collection at various stages of the supply chain usher in a new era of big data (Ciampi et al., 2021).

The concept of supply chain refers to the flow of information as well as goods and money (Behl et al., 2022). Through technology adoption, they have the provision of the ability to monitor information flows and are willing to collect and analyze various types of data for proper management (Awan et al., 2022). A typical distribution system must handle data flows in excess of 100 gigabytes per day (Dehghanpour et al., 2018). In fact, approximately 90% of the evidence available today is recently generated by humans (Wang et al., 2020). The number of Internet devices in cars, shops and transportation is increasing by 30% per year (Shen et al., 2018), and it is believed that sensor-based technology can significantly reduce operating costs by 10 to 25 times. % (Bhattarai et al., 2019). Digital data is growing rapidly and is expected to reach 35 Zeta bytes by 2030 (Nie et al., 2020).

In the current scenario, organizations are increasingly aware of data quality and advanced analytical tools (Piprani, Ali and Shah, 2022). The BDA has the potential to manage the Third Industrial Revolution (TIR), as well as digital production services, mass production and customization (Özemre and Kabadurmus, 2020). The use of BDAC technology can improve organizational capabilities in a rapidly changing market environment (Chiroma et al., 2021). However, to successfully deal with the diffusion of BDA technology in the supply chain, organizational and behavioral issues related to adoption and use need to be addressed (Chong et al., 2021). Empirical studies have examined the impact of BDA capabilities on supply chain management (Arunachalam et al., 2018; Mandal, 2018; Jha et al.,2020). Despite its popularity in the industry, many organizations are reluctant to invest in BDA capability technology due to lack of understanding of its benefits (Arunachalam et al., 2018). Furthermore, research on the feasibility of BDA in supply chain innovation is limited, and a comprehensive BDA feasibility study is needed to exploit the benefits of big data in supply chain innovation. Business uncertainty can increase competitive pressures, as firms face institutional uncertainty that forces them to develop new ideas and compete in the market (Mageto, 2021).

Innovation in supply chain business has become a good idea to be competitive and helps organizations and businesses to create new strategies (Sabahi and Parast, 2020). Due to outdated practices, inadequate security, and lack of appropriate resources in developing countries organizations face this challenge (Sabahi and Parast, 2020). Organizations operating in developing countries need to change their systems and should adopt new methods in their processes, innovation integration will eventually change the organization's performance and the firm will gain a competitive advantage (Yang and Lin, 2020). Supply chain innovation helps organizations generate new ideas and those ideas can be implemented into supply chain processes that help organizations become more competitive (Ashrafi and Zare Ravasan, 2018). Organizations improve their performance in the areas of operational efficiency, service efficiency, and economic participation, social responsibility, and environmental protection with the help of new asset management systems (Soltani et al., 2019). The purpose of supply chain innovation is to introduce new technologies that improve supply chain performance (Wong and Ngai, 2022).

Market insecurity and business uncertainty have pushed firms to improve their supply chain through innovation (Afraz et al., 2021). Innovation is necessary for strong competition (Afraz et al., 2021). Innovation can increase the value of an organization, increase its demand, and reduce its costs. Meanwhile, businesses face challenges in managing and using innovation effectively (Ali and Ahmed, 2022). The industry's ability to expand operations and its supply chain structure, will allow its firms to respond quickly and improve supply chain processes (Shamout, 2019). According to Soltani et al. (2019), the importance of information exchange in the supply chain is emphasized. Based on

Fernando et al. (2018) a firm maintains customer preferences and increases quality by exchanging information in its supply chain. Information sharing improves relationships between all levels of the supply chain, as well as between the organization and the end customer (Alzoubi and Yanamandra, 2020).

Learning orientation is a strategic business process in which innovation and market entry decisions involve practices, processes and activities (Ojha, et al., 2018). It can be defined as the innovation, agility and risk of an organization in the formulation and implementation of strategy (Iyer et al., 2019). Innovation reflects a firm's willingness to explore new ideas and participate in the development of new strategies aimed at developing new products and services (Mandal and Saravanan, 2019). Proactivity reveals that an organization is willing to recognize and exploit promising market opportunities ahead of competitors (Habib et al., 2020). Risk-taking attitude represents the level and degree of willingness of business resource managers to spend projects aimed at implementing uncertain outcomes and high failure costs (Yeniyurt et al., 2019).

Companies committed to learning principles try to encourage their employees to make autonomous decisions, actively innovate, take calculated risks, act fast and act more aggressively in competing with competitors with the support of relevant data (Jiabin et al., 2021). The logical reason for studying the role of this particular strategic approach in a data-driven context is often the high complexity of decision-making (Afifa and Nguyen, 2022), which will provide the right ability to reason and support can be controlled through decisions BDAC, which can help strengthen the organization's attitude to challenging and risky behavior (Dubey et al., 2020). These papers highlight the significant impact of learning orientation on product and process innovation with the help of BDAC (Dubey et al., 2020; Afifa and Nguyen, 2022; Jiabin et al., 2021). These unique features make it possible to combine student orientation processes with greater skills in data analysis, which primarily refers to an understanding of market changes, learning and challenges, with the ability to redesign and innovate tools is (Benzidia et al., 2021). Based on the classification of the big capacity of data analysis presented by Dubey et al.(2020) the learning orientation process can be linked to the upper levels, because it receives the power from the lower levels to guide the companies to change of processes and systems required to achieve competitive advantage to sustain and improved supply chain innovation (Jiang and Shen, 2018; O'Connor et al., 2018; Bhatti, Rehman and Rumman, 2020).This current study is aim at examining the mediating effect of learning orientation of Big Data Analytics Capabilities on Supply change innovation in Ghana.

1.2 Problem Statement

The recent emergence of the Big Data (BD) phenomenon has led organizations to focus more on managing internal and external data with the aim of seizing new opportunities to maintain their competitive advantage (Dubey et al., 2019). BDAC has been described as the next frontier of creativity, competitiveness and creativity (Shokouhyar et al., 2020). Using customer-generated BDAC, organizations have the opportunity to implement immediate, user-centered innovation and user-driven innovation (Mikalef et al., 2019). The first uses customer analytics to analyze the characteristics, standards, and needs of voluntary Internet users with the aim of improving Internet users' expectations for innovation (Hooi et al., 2018).

On the other hand, user-driven innovation requires companies to innovate together with individual customers to drive and implement initiatives to build value partnerships (Bahrami et a., 2022). In both cases, the use of BDAC assumes strategic value in order to replicate the relationship between the firm and the customer, thus representing the basis of the sustainable value cycle of both parties (AlNuaimi et al., 2021). The ability to pursue other new business opportunities through BDAC (Lee and Mangalaraj, 2022) continues to disrupt business concerns in many industries (Awan et al., 2021; Chen et al., 2019; Luthra et al., 2018; Singh). et al., 2019; Lutra et al., 2018; Singh et al., 2019). Thus, many scholars emphasize the importance of studying the impact of digitalization on Supply chain innovation (Tavana et al., 2020; Lee et al., 2018; Jirasatjanukul et al., 2019). In fact, today's organizations can use BDAC effectively both internally and externally (Fosso Wambabet al., 2018). For example, BDC can be used to create supply chain innovations by improving business relationships with customers and other stakeholders (Ciampi et al., 2021); creating new value propositions where data supports or leads data through revenue generation (Behl et al., 2022); and inventing ways to capture their value, e.g., adding new revenue streams or reducing cost projects (Dehghanpour et al., 2018).

In addition, more and more businesses and industrial networks seek to gain a long-term competitive advantage by using the latest digital technologies to modernize their business processes rather than replace existing products. themselves, services and/or processes (Piprani, Ali and Shah, 2022).

Given the opportunity to collect, analyze and use large, diverse and rapidly generated data to support decision-making, many organizations have made significant efforts to improve business-related infrastructure, technology, expertise and adopted practices (Özemre and Kabadurmus, 2020). Although important, Big Data Analytics Capabilities (BDAC), tools that analyze data and visualize results to support decision-making, are not sufficient to transform organizations to effectively transform data into knowledge in data-driven organizations (Chiroma et al., 2021). Big Data Analytics Capability (BDAC) refers to a company's ability to generate data that surpasses competitors through supply chain innovation through technology and capabilities (Chong et al., 2021). However, for the best analysis in the literature, there is still no empirical work in the innovation management literature investigating the impact of BDA adoption on supply chain innovation

(Arunachalam et al., 2018; Mandal, 2018; Jha et al . , 2018). 2020 is there). It is based on the literature describing how BDAC and integrated offering innovation can be studied to create transformative value in the orientation of today's students. The literature highlights research on Big Data Analytics Capabilities (BDAC) (Akter et al., 2016; Mikalef et al., 2020; Albergaria and Jabbour, 2020; Ciampi et al., 2021; Xiao et al., 2020), Supply Chain Innovation (SCI) (Dubey et al., 2019; Mikalef et al., 2020; Lee and Mangalaraj, 2022; Mandal, 2018; Sabahi and Parast, 2020; Yang and Lin, 2020) and Learning Orientation (LO) (Ojha et al., 2018; Iyer et al., 2019; Mandal and Saravanan,2019; Habib et al., 2020; Jiabin et al., 2021; Afifa et al., 2022) but they have not been intensive study on how the three variables contribute to each other to helps firms compete among themselves in this new age of technology. This has been a gab in literature making Bid Data Analytics not using it capabilities to enhance supply chain innovation through the help of learning orientation. For this reason, the current study wants to contribute to already existing the field of Big data Analytic Capabilities (BDAC), Supply Chain Innovation (SCI) and Learning Orientation (LO) by examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana.

1.3 Objectives of the study

The main objective of the study is to examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The specific objectives are as follows;

1. To determine the effect of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana.
2. To investigate the contribution of big data analytics capabilities (BDAC) on learning orientation (LO) in Ghana.

3. To investigate the effect of learning orientation (LO) on supply chain innovation (SCI) in Ghana.

4. To determine the mediating effect of learning orientation (LO) of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana.

1.4 Research Questions

1. What is the effect of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana?

2. What is the contribution of big data analytics capabilities (BDAC) on learning orientation (LO) in Ghana?

3. What is the effect of learning orientation (LO) on supply chain innovation (SCI) in Ghana?

4. What is the mediating effect of learning orientation (LO) of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana?

1.5 Significance of the Study

The contribution of this study is twofold. In particular, it demonstrates the direct impact of BDAC in creating SCI value, providing feedback, and selecting new and effective paradigms for product development. These results enrich the BDAC and SCI governance literature by strongly affirming that institutional structures can support the evolution of robust, profitable, and innovative business models for proper implementation of BDAC, especially in changing contexts. Second, the study shows that BDAC directly impacts SCI by encouraging firms to make innovative and risky decisions about learning, such as developing market information systems, collaborative external and internal knowledge sharing, infrastructure and decision-making is being managed.

Regarding SCI, BDA capabilities enable businesses to explore other options when faced with supply chain uncertainty (Akter et al., 2016; Mikalef et al., 2020). This will guide managers to a deeper understanding of the complementary assets and capabilities needed to fully utilize data analytics capabilities to improve supply chain innovation and gain competitive advantage in their disciplines. The literature on the potential influence of BDA abilities on learning appears to have grown in recent years. In order to obtain theoretical and practical implications, it is important to understand how the artifacts of the large capacity of data analysis produce competitive advantages and how these effects occur (Albergaria and Jabbour, 2020). According to some researchers, the effect of BDA capabilities on supply chain improvement and learning is not specific because it is linked to other organizational capabilities (Ciampi et al., 2021; Xiao et al., 2020). Moreover, some say that investing in this sector does not always pay off, only a few businesses benefit from the potential of BDA (Gupta and George, 2016). But this study will bring the benefits of BDAC, SCI and Learning to business managers, policy makers and academics.

1.6 Research Methodology

The main objective of the study is to examine the mediating role of learning orientation (LO) on big data analysis capability (BDAC) on supply chain innovation (SCI) in Ghana. Therefore, the research that will be carried out is based on the philosophy of positivism, which allows a philosophy that is true and can be repeated, and the results of the described relationships are observed. The nature of the study is to ask systematic and statistical questions of the relationship between the aforementioned types of BDAC, SCI and LO. The use of statistical analysis to make the results allowed for freedom on the part of the researcher, which produced objective research, which explains the cause-and-effect relationships between the measured variables.

. The population will include organizations from different industries and of different sizes, due to the indirect use of data and information derived from them. No eligibility criteria will be placed on the amount of data stored, or the amount of information generated by the organization. Reducing the number of people in defining data production, storage and use standards will reduce the data created for research, while the amount of data produced and processed worldwide is growing and making those parameters are left out quickly, to reduce the lifetime of the discoveries.

Deductive reasoning will be used as a research design to confirm or challenge existing theories and provide general findings related to the relationship to be tested (Markovits, et al., 2018). A questionnaire will be designed and used to collect data that will be typical of a descriptive study, which seeks to describe and explain the characteristics of the sample, to verify the theory used as the basis of the theory, therefore suitable for planning purposes. Three hundred and twenty-seven (327) firms will be selected using purposive sampling technique with the help of Cochran's (1977) formula of sample size determination. For the data analysis, the data will be analysis in SPSS which will include missing values, validity, explanatory statistics, and hypothesis testing for multi-dimensional analysis. Subsequently, the data will transferred to version 4.0 of SmartPLS (Sarstedt and Cheah, 2019; Hair et al., 2020) to perform predictive calculations through multivariate data analysis. Which will help examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The results will be displayed using tables, graphs and charts.

1.7 Scope of the Study

Even though has been several issues in the Ghana in recent times, this study focused on the effect examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. Since BDAC and innovation in supply chain is broad, this study will focus on blinding learning orientation with them to get their effect on firms in Ghana. The choice of firms hinges on the fact that they are knowledge driven. The researcher intends to conduct research among firms across Ghana.

1.8 Limitation of the Study

As with any research, the present study is not without limitations. Firstly, this will be conducted only in Ghana thus the results of this study do not necessarily reflect firms' opinions in other countries. Again, it is not clear whether the outcome will have the same effect on the mediating role of learning orientation (LO) of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana as in another context since it may be possible that the needs and perceptions of firms in other countries may differ due to different levels of knowledge, and experience. More so, the factors that measured positive significant influence on Supply chain Innovation may prove otherwise in other countries. Secondly, the outcome of the study dwells on cross-sectional data and it covered the views of the sampled firms at a specific period of time. Meanwhile using a cross-sectional strategy limits the study's capability to examine the role of study variable over a period of time.

This research will make use of quantitative techniques in data collection and analysis. The use of a questionnaire will offer very valuable information on the subject matter, however, using qualitative data such as interviews could also offer more detailed information on the topic. The research will collect data from firms through quantitative means alone which gives very important information to the study, however collecting data from firms through purely qualitative means will also be proper to unravel much broader views on the topic.

1.9 Organization of the Study

This first chapter, also named as the introduction, has expanded the background to the study, the statement of the problem, the study objectives, and their corresponding research questions or hypothesis. The significance of the study, and the scope of the study. It has as well explained the brief methodology of used in this study. The chapter ends with the structure of the thesis proposal. Chapter two reviews the relevant literature from previous research. The chapter also expounds on the key concepts and reviews empirical research related to them. Finally, the chapter ends with a summary highlighting identified gaps in the literature. In the nutshell, this chapter will explain the theoretical concept of the study as well as the development of the model based on previous studies. Chapter three describes the methodology to be used for this research, including research design, population, sampling design, and the development of survey instruments to measure the constructs in the research model. The chapter also presents tools to be used in analyzing the data and ends with ethical considerations germane to the study.

Chapter four presents and discusses the results and analyses from the data gathered. It covers the response rate, preliminary data analysis, and respondents' demographic characteristics, descriptive analysis of variables, inferential analysis, exploratory factor analysis (EFA). The chapter also presents the evaluation of Partial Least Square-SEM results, structural model analysis, and hypotheses testing. The final chapter five discusses of research outcome, the contribution of the study, limitations of the study, implications of the study, and conclusions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the related literature on the study. The focus is on conceptual, theoretical underpinnings, empirical studies and development of hypothesis.

2.2 Conceptual Review

2.2.1 Big Data Analytics Capability

There is growing disagreement over the value of big data analytics in advancing an organization's strategic objectives (Davenport, 2006; Manyika et al., 2011; Prescott, 2014; Mishra et al., 2016, 2017; Roden et al., Ji-fan Ren et al., Choi et al., Fosso Wamba, 2017; Jabbour et al., 2017), but there isn't agreement on how to organize (Galbraith, 2014). We make the argument that big data is defined as data whose volume, rapidity, and diversity make it challenging for an organization to manage, evaluate, and extract meaningful insights using predictable and traditional approaches. We base this definition on Manyika et al.

"Analytics" is the process of deriving useful insights from data through the production and distribution of reports, the development and use of statistical and data-mining models, the exploration and visualization of data, as well as other approaches (Grossman and Siegel, 2014, p.20). We can therefore contend that big data analytics capability is an organizational ability with tools, methodologies, and procedures that allows the organization to process, envision, and analyze data and produce understandings that enable data-driven operational planning, decision-making, and implementation (Srinivasan and Swink, 2017). Big data analytics capabilities in the context of supply chain management enable businesses to explore options connected to demand and supply uncertainty (Waller and Fawcett, 2013; Hazen et al. 2014; Wang et al. 2016).

Because the ability to analyze massive volumes of data and extract relevant information has led to a revolution in a variety of industries, BDAC has recently drawn the attention of many researchers (Bilal et al., 2016). According to some academics, BDAC can be utilized to address a variety of problems, could change the game, and would considerably boost company performance (Wamba and Gunasekaran, 2017; Jeble and Dubey, 2017; Gupta and George, 2016). In actuality, BDA systems boost organizational agility and give businesses a competitive edge over rivals (Côrte-Real and Oliveira, 2016). Considering the study by Ajayi et al. (2019), which evaluated the connection between the BD platform and safety accident prediction. The findings of this paper demonstrated that information management had significantly improved. Wu et al. (2015) demonstrate that BDAC can be incredibly beneficial for understanding ambiguous situations and uncertainties (Wu et al., 2015).

Predictions can be made using BD analysis. The framework, known as big data predictive analytics, greatly enhances the supply chain's operational and strategic capabilities (Hazen and Skipper, 2018). Future BDA system opportunities and difficulties must also be considered (Zhong, 2016). Consequently, it is crucial to comprehend the various BDA frameworks and their types and constructs (Nguyen et al., 2016). Five BDAC were found by Wang and Kung (2018) after conducting content analyses on a number of BD implementation cases in the healthcare industry. They identified five BDAC, including analytical capability for patterns of care, unstructured data analytics, decision support, predictive capability, and traceability. They also offered a number of recommendations for healthcare institutions.

Additionally, acquiring BD on its own does not equate to acquiring valuable and instructive data because effective analytical techniques and tools are needed to interpret BD correctly and produce information of the highest caliber (Jeble and Dubey, 2017; Gupta and George, 2016; Bowman, 2018). It is crucial to take into account how statistics and machine learning might be effective tools for analyzing BD (Torrecilla and Romo, 2018; Iniesta et al., 2016). The effect of various statistical methods to examine the data acquired on environmental issues was discussed in research to demonstrate that statistics is a powerful instrument to deal with BD. They claimed that BDCA could raise people's quality of life (Gupta and Mateu, 2018). However, a common issue faced by many statisticians is that they are unsure of where to begin or how to approach BD (Qing Shi, 2018).

2.2.2.1 BDAC Methods

Supply chain firms require effective methods for turning massive amounts of diverse data into actionable information in order to support evidence-based decision-making (Gandom and Haider 2015). Using BD has endless potential. However, it is constrained by the lack of BDAC-specific technology, tools, and capabilities. This is feasible given that BDAC may improve decision-making and raise supply chain working output when a variety of analytical techniques are employed to make sense of the data. The results for BDAC methodologies broken down into predictive, descriptive, and prescriptive analytics are summarized in the description that follows.

Application of predictive analytics models represents the primary contribution of BDAC research to the field of SCI. This analytics approach relates to anticipating future events, such as the best delivery time, specific customer behavior, forecasting demand, anticipating shortages and out-of-stock situations, anticipating equipment failure points, and anticipating sales performance (Kumar et al. 2016). The results of the study show that data mining algorithms (such as decision trees, clustering and classification algorithms), statistical methods (PLS-SEM used by Akter, Fosso, and Dewan (2017), hidden markov models, and cost minimization algorithms), machine learning, fuzzy logic approach, visualization techniques (RFID-cuboid model), logistic regression modeling, optimization techniques, and sentinel analysis are the common methods used in the predictive analytical approach.

Seven research articles, or an explanatory definition of fault and a success condition, were taken from the total of 88 papers that were extracted. They used descriptive approaches for gathering and analyzing data describing current and past events, individual product functions, and product features to determine the root of the problem. By gathering and analyzing tweet data on beef products, for instance, to determine what consumers like and dislike, supply chain activities can be tracked back and the waste they cause can be reduced (Mishra and Singh 2018). Bhattacharjya, Ellison, and Tripathi (2016) discuss another potential application of descriptive BDAC to explain the complexity of logistics-related interaction between e-retailers and their customers on social media platforms and increase consumer base outreach. Descriptive statistics, data mining, and mathematical model techniques have all been used in research papers relating to descriptive analytical approaches.

It is clear from our SLR analysis of 88 articles that prescriptive analytical approaches have received more attention recently (Tayal and Singh 2018; Nnamdi 2018). Prescriptive analysis was primarily used in manufacturing to quickly identify, recognize, and diagnose faults and irregularities (Chien, Liu, and Chuang 2017). However, due to the need for highly qualified personnel and more sophisticated tools, this strategy is still being researched and investigated.

2.2.2 Supply Chain Innovation

Innovation in the supply chain has been defined from a variety of angles. For instance, Flint et al. (2015) focused on innovation that is particularly supportive of customers for a better and new service. Although the connected publications on innovation themselves emphasize the importance of processes and technology in generating successful ideas, Chesbrough (2019) draws emphasis to the value of innovation philosophy in accessing creativity (Kahn, 2016; Christiansen, 2017). There are other references to the ways in which markets and businesses innovate (Chesbrough, 2018; Rogers, 1995). Businesses continue to grow as they develop and research novel concepts, goods, and services. According to Drucker (2015), innovation serves as a tool primarily for business owners. Innovation was defined as "a procedure of spinning prospects into novel ideas and situating these into widely used practice" by Afuah (2018). By developing new technical skills and knowledge, innovation enables the development of cutting-edge goods and/or services that satisfy the needs of consumers. Supply chain innovation is essential for service providers to ensure the delivery of valuable services (Chapman et al., 2016).

Although innovation emphasizes idea generation, it is not valuable or intended to be a supply chain essential, but it produces something precious for the customers. Therefore, a supply chain innovation endeavor, performance, or entity is one that a person or additional entity of espousal claims to be current. The development of supply chains does not need to be novel to humanity. It might, however, lead to the corporation offering a fresh service to its clients. A supply chain is a group of companies involved in converting raw materials into finished products and services and distributing them to end users (Johnson, 2016).

It needs to be managed as efficiently and cheaply as possible. Companies are forced to innovate by both competitive pressures and challenging economic conditions. For businesses to respond quickly to swift changes in products and services, as well as customer demand and issues, innovation is essential (Kim et al., 2015). Similarly, innovation is improvements to how information, relationships, and products and services move within a network that businesses must make in order to survive (Osterwalder and Pigneur, 2017). Innovation primarily occurs within organizational structures, processes, technologies, services, and strategies (Rogers, 2018). For businesses attempting to increase the viability of their SC systems, the effective operation of SC is particularly crucial (Azevedo, 2018). Accordingly, SCI causes time and cost savings, resulting in distinctive functioning approaches and a reliable conveyance framework for adjusting to changing business conditions (Lee et al., 2016). According to Lee et al. (2003), service sectors should focus on SCI for a compelling conveyance service. According to researchers, supply chain innovation enables businesses to maintain their competitive advantage and improve supply chain performance (Flint et al., 2015; Franks, 2016; Krabbe, 2017; Lee et al., 2019). Additionally, it is acknowledged that supply chain innovation can improve operational performance and increase service viability (Arlbjrn, 2016). Specifically, SC innovation comprises adjustments to products, processes, or services that either increase productivity or advance the happiness of the ultimate consumer, as well as technology-improved processes and strategies within the outbound SC (Seo et al., 2014). It is essential to enhance global supply chain management inside logistic networks because suppliers, team members, managers, and leaders must develop enduring ways to reduce supply chain interruptions (Varzandeh et al., 2016).

2.2.2.1 Dimensions of Supply Chain Innovation

Demand Planning: Because it plays a supporting role in operational processes like inventory decision-making and production planning, accurately forecasting demand is one of the most significant challenges in the field of operations management (Jain, Rudi, and Wang 2015). On the other hand, demand planning is a crucial component of SCI planning, according to Wang et al. (2016), as it aids in forecasting future demand and sales using data from current sales, marketing, and inventory information gathered cooperatively by supply chain partners. According to Hosoda and Disney (2012), the main obstacle to demand planning is the existence of time lags in information flow, which can be interpreted as a lack of stock level visibility, sales data availability, visibility of customer needs, and market segmentation. By including any anticipated extraordinary factors together with their potential effects on sales in the official demand predictions, it is feasible to move from demand forecasting to demand planning.

Production and Manufacturing: In an effort to increase profits, businesses maximize their manufacturing by reducing lead times, lead-time waste, and production costs while still meeting client demand. Integrated production, which includes distribution, inventory, and demand modeling, is the aspect of production that has been the subject of the greatest research (Eksioglu, Edwin Romeijn, and Pardalos 2006). In most manufacturing businesses, integration of production with other operational tasks in the supply chain is essential to achieving optimal operational performance (Chen 2010). Due to the expanding product diversity, manufacturing processes have become more complicated, necessitating careful design and efficient manufacturing networks (Mourtzis 2016).

Business managers typically optimize their production in order to increase profits by overcoming the following obstacles: decreasing production waste, ensuring the sustainability of products and processes, cutting the lead time, anticipating and preventing production disruptions, and lowering production costs to meet customer demand (Pal, Sana, and Chaudhuri 2014). Making green manufacturing and production a priority is motivating decision-makers to think about energy consumption and explore methods for achieving energy-efficient production management (Irani et al. 2017; Chawla et al. 2020). Because of this, energy reduction in manufacturing processes presents another difficulty.

The procurement processes that link manufacturers and suppliers provide the vital connection between the source of supply and the business as a whole (Zhou et al. 2014). Managers have been told that one of the biggest challenges in the procurement process is selecting dependable vendors (Lamba and Singh 2017). A key factor in the success or failure of a business is the performance of suppliers in terms of the cost of the component components, raw materials, and services purchased (Trivedi et al. 2017). The order allocation determination process, which determines various quantities of materials from various suppliers, plays a vital part in enhancing the firm's cost effectiveness in addition to selecting the appropriate provider (Trivedi et al. 2017). In order to establish trade-offs between qualitative and quantitative factors, suppliers are assessed on a variety of performance attributes and criteria (Nazari-Shirkouhi et al. 2013).

Inventory in the supply chain includes all of the components needed at both the upstream and downstream levels. One major issue for inventory is the lack of information visibility for responsiveness and traceability. Time-based competition, one of the sources of competitive advantage in supply chains, makes efficient inventory management very difficult (Wu and Yang 2012). The cost of inventory is thought to be an extremely expensive operation that necessitates routine stock audits, whereas the ideal level of inventory is one that maximizes supply chain profitability (Chopra and Meindl, 2010). Uncertainty in demand and supply will present difficulties for the safety inventory, including capacity limitations, production and delivery delays, and an increase in customization. Additionally, maintaining an organization's standing in the market requires meeting demand that is higher than what is anticipated for a given period.

The degree of customer satisfaction has increased as a result of globalization, online businesses, and a variety of other factors. This has increased the demand for goods with the best quality, lowest price, quickest delivery time, and best overall experience. With regard to logistics specifically, some academics frequently create knowledge-based logistics systems to suggest optimization models for logistical challenges in the face of future uncertainty and to talk about the roles of logistics capabilities, analytics, and business performance (Yu and Li, 2000; Mikalef et al., 2019b)

2.3 Theoretical Review

Task-Technology Fit Theory (TTF) and Institutional Theory are both integrated into this study. According to TTF theory, a new technology is actually used and produces gains for performance when its features match those of the task at hand (Lai et al., 2018). On the other hand, institutional theory, which looks at the causes of isomorphism represented in three dimensions of institutional pressures—coercive pressures, normative pressures, and mimetic pressures—provides a thorough understanding of the intention behind the adoption of practices and their implementation (Dubey et al. 2017).

2.3.1 Task-Technology Fit Theory

TTF is built on the premise that IT improves both individual and organizational performance when the task's requirements and the technology's capabilities align (Goodhue and Thompson 1995). When the functionalities of technology and the task requirements are in harmony, IT has a positive effect on performance, according to their research. Furneaux (2012) connected the TTF theory to the contingency theory, which contends that the organization should determine the fit between practices and the environment in order to improve performance. The TTF theory is based on the idea that the degree of fit between a technology's qualities and a task's requirements will determine how motivated users are to adopt that technology. The impact of TTF on the use of technology causes the effect of fit on performance to occur either directly or indirectly (Furneaux 2012). We identify some IT capabilities relevant to the BDA approach expressed in prediction, description, and prescription in order to operationalize the TTF theory (Mikalef et al. 2019a).

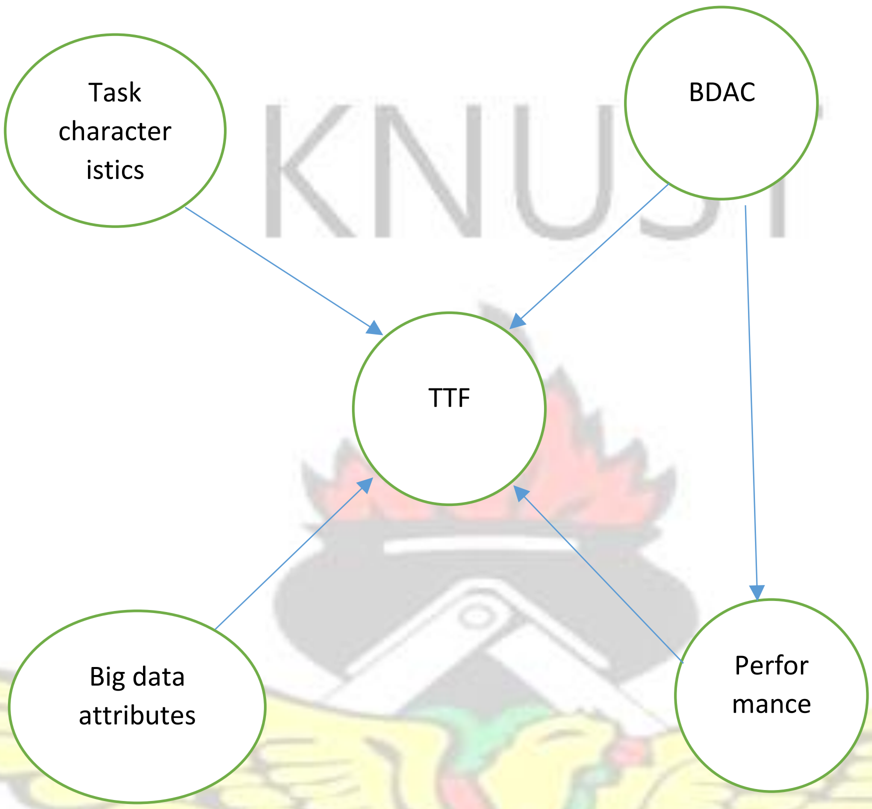

Figure 2.1: TTF-BDA attributes framework

We created tasks derived from examining literature in the context of SCI in order to determine the SCI portfolio of tasks, and we then categorized the necessary tasks as follows:

- Information quality is essential to a successful information system.
- Achieving the ideal inventory level, cutting inventory expenses, and maintaining the necessary level of customer service.
- Innovative goods and services can be quickly introduced to the market by outsourcing logistical tasks.
- The best resources operate to guarantee that all manufacturing procedures are in control.

- Generalized product design and quality control are two examples of product design.
- Sales now casting to reduce demand uncertainty and find the best inventory option.
- Enhancing the procurement process enhancing market segmentation and customer needs visibility deciding how to distribute items and the locations of distributors.

The use of BDA and organizational performance may be directly impacted by the alignment of the task portfolio of SCI and the BD characteristics. To determine the overall performance, we link the TTF theory to the BDA attributes and BDA usage in Figure 2.1.

2.3.2 Institutional Theory

According to the theory, social behavior is governed by the procedures by which structures (such as customs, norms, rules, and schemas) are established (Scott, 2005). In order to explain the direct performance effects of big data predictive analytics on organizational performance, Dubey, Gunasekaran, Childe, et al. (2019) used this theory. In order to be accepted and ensure long-term survival, organizations and organizational actors strive to establish legitimacy, status, and reputation in their environments (Mignerat and Rivard 2009). Additionally, organizations are required to choose safer technologies that can abide by social pressures rather than economic benefits (Dubey, Gunasekaran, Childe, et al. 2019). The institutionalization process and institutional impacts are the two topics that institutional theory has looked at (Pishdad, Koronios, and Geursen 2014). The institutional impacts of coercive, mimetic, and normative isomorphism are the main topic of this study.

Coercive isomorphism is a result of both formal and informal external pressures from other organizations as well as from cultural norms in the society that organizations are a part of (Dimaggio and Powell 2000). Global organizations play a significant part in changing customer expectations and increasing customer satisfaction, which has increased the demand for products with the best quality, lowest price, quickest turnaround time, and best delivery service. These factors all put more pressure on businesses to use sophisticated analytics tools to analyze data from customer location, hits, browsing behavior, and shopping carts in order to implement precise customer assessment, personalize services, and customize products (See-To and Ngai, 2018).

When there is symbolic uncertainty in the environment, organizational ambition to mimic other organizational behaviors results in mimetic isomorphism (Dimaggio and Powell 2000). Mimesis, a strategy to lessen uncertainty and improve predictability, is more common in anxious behavior than in rational behavior (Pishdad and Haider 2013). The bullwhip effect, which refers to demand and supply unpredictability as well as uncertainty regarding timely delivery of goods as raw materials or completed products, is one of the major difficulties in SCO that affects operating efficiency and results in issues (Bag 2017). There is considerable uncertainty at every stage of the supply chain, which means that the causes of uncertainty are not just the ones described above. A mimetic predictive analytics tool must be used to identify patterns in future events and create forecasts as a result of the increasing level of uncertainty.

It results from professionalization. Normative isomorphism (Dimaggio and Powell 2000). Normative pressures evaluate whether an organization performs in a desirable manner in order to take into account the moral aspect of legitimacy (Pishdad and Haider 2013). Normative pressures imply that organizational strategic decisions are influenced by the shared values and norms of members of their social networks, including inter-organizational channels between suppliers and customers (Son and Benbasat 2007). Several normative pressures pertaining to environmental issues, personal safety, and supply chain sustainability are present in the SCI context. Making informed operational decisions is therefore a crucial step that organizations must take if they want to carry out their operations effectively in this new, shifting environment. This can be done by altering proactive strategy formulation and BDA-based decision-making.

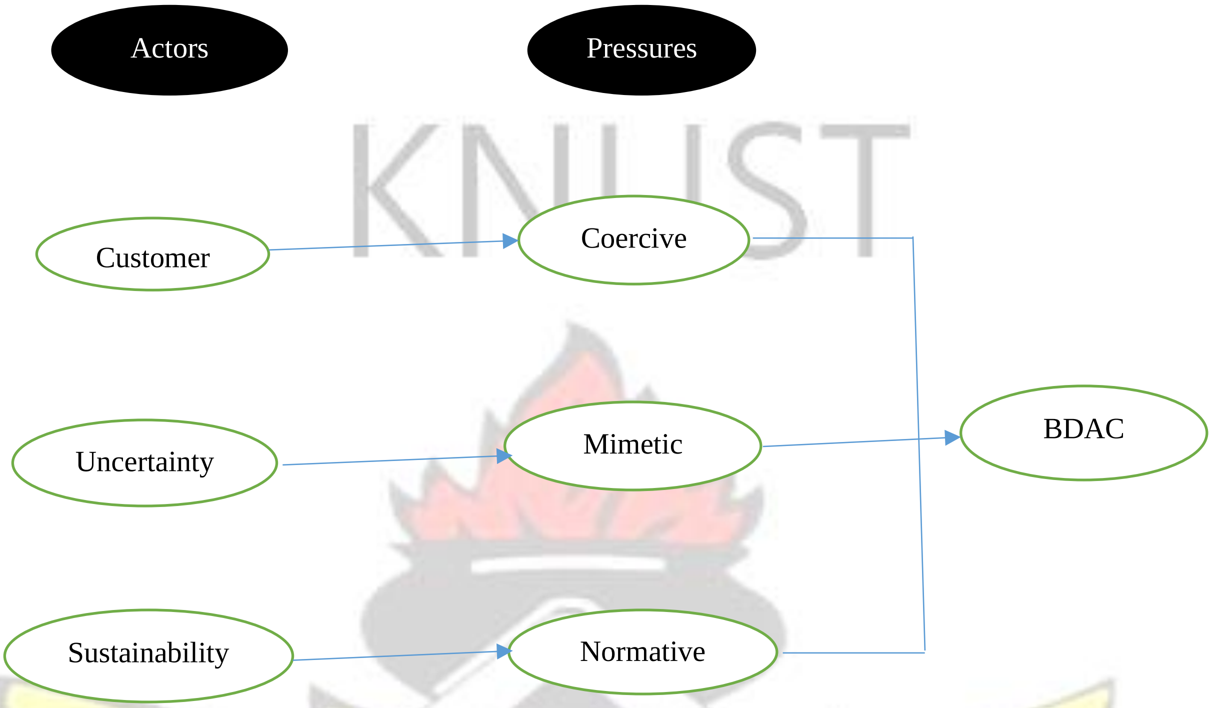

Figure 2.2: Institutional theory and BDAC framework

2.4 Conceptual Framework

The conceptual framework and presumptions that are consistent with BDAC, supply chain innovation, and learning orientation are described in this section. The study looks at how BDAC affects supply chain innovation.

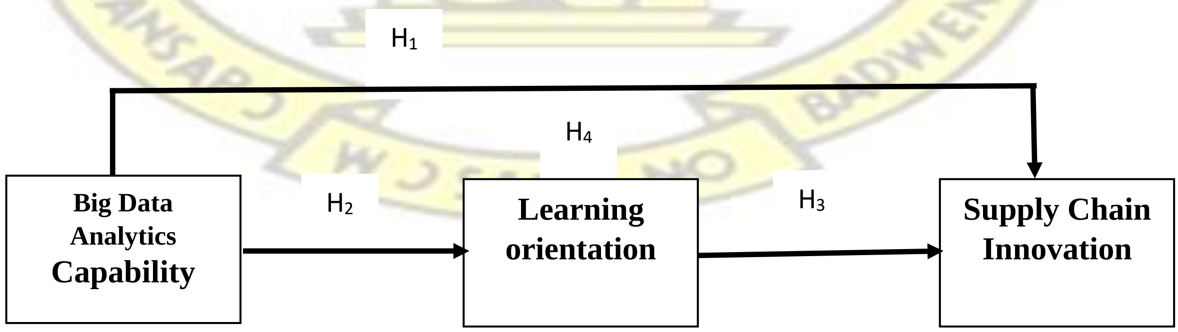

Figure 2. 1: Conceptual framework

2.5 Empirical Review

Sajjad et al. (2019) used 234 pharmaceutical companies in their study to examine the influence of big data analytics capabilities on supply chain sustainability in Iran. A standard BDAC questionnaire and an online supply chain sustainability self-assessment from the United Nations (UN) were used in the study. The study shown that BDAC has a significant impact on the internal, vision, and engagement dimensions as well as the sustainability of the pharmaceutical supply chain. The relationships between BDAC and the other aspects of supply chain sustainability, such as expectations, scope, and goals, are discovered to be positive but not statistically significant.

A study on the critical analysis of the effects of big data analytics on supply chain operations in the United Kingdom was carried out by Ruaa et al. in 2022. They come to the conclusion in their studies that SCO and BDA can enable the dynamic capacities of companies, enabling decision-makers to improve the capabilities of the corporate or company or to better sense future opportunities and risks.

Deductive reasoning and quantitative analysis were used in the study. Structural equation modeling was used to collect data from 243 UK manufacturing companies via survey questionnaires. The research found that while learning orientation affects operations strategy and supply chain integration, innovation performance is not directly impacted. Additionally, while cost and delivery strategies have a negligible impact on these variables, quality and flexibility strategies have a positive effect on innovation performance and supply chain integration.

In a paper titled Big Data Analytics Capability in Supply Chain Agility: The Moderating Effect of Organizational Flexibility, Dubey (2018) examined this topic. The study used a pre-tested questionnaire to collect 173 valid replies. Their findings imply that the capacity to use big data analytics positively and significantly impacts supply chain agility and competitive advantage. The researchers' findings also corroborated their hypothesis, according to which organizational flexibility has a beneficial and significant moderating influence on the pathway connecting supply chain agility and big data analytics competence. They could not, however, find evidence to support the idea that organizational flexibility has a moderating influence on the relationship between competitive advantage and big data analytics capabilities.

A study on big data analytics in sustainable supply chain management, with a focus on manufacturing supply chains, was conducted by Mageto in 2021. Toulmin's argumentation model is used in this conceptual paper to review pertinent literature and reach conclusions. The study names data processing, analytics, reporting, integration, security, and economics as the components of big data analytics. Transparency, a culture of sustainability, corporate objectives, and risk management are components of sustainable SCM. It is known that BDA improves manufacturing supply chains' SSCM. Challenges to BDA implementation include cyberattacks and a skills gap in information technology.

In a study published in 2022, Ghazal et al. sought to determine the influence of organizational flexibility and supply chain resilience as mediating factors in the relationship between data analytics capabilities and competitive advantage in the textile industry. In order to study the linkages, a new conceptual model was created, and partial least squares-structural equation modeling (PLS-SEM) was used for analysis. Four well-known sleep product manufacturers and 450 qualifying participants made up the study's population. In addition, before the questionnaire was utilized for the final survey, a trial survey with 30 participants was conducted.

According to the findings, organizational flexibility, supply chain resilience, and competitive advantage were all positively impacted by data analytics capability. Furthermore, organizational flexibility and supply chain adaptability played mediating roles in the connection between data analytics capability and competitive advantage. Top managers will find some management insights that are presented interesting.

A study on the relationship between innovation, market orientation, and performance: the mediating role of innovation was carried out by Lartey et al. in 2020. The study's main objective was to look into the relationship between performance and innovation. The study uses a structured questionnaire to collect data from a 300-person sample. The relationship between innovation and performance was examined using a structural equation model, and the relationship between market orientation, innovation, and efficiency was determined using innovation as a mediator. The results demonstrate how innovation affects performance. Market orientation and creativity have a strong and significant correlation, which ultimately improves firm efficiency. By confirming the link between innovation and performance using the innovation types, the study has an impact on the body of existing literature.

A study on big data analytics in supply chain management: trends and associated research was done by Rozados and Tjahjono in 2016. According to the report, SCM Big Data are mostly unconnected huge information silos that are dispersed among business functions and external sources. As a result, they do not offer end-to-end visibility of SCM. The majority of enterprises must work to make diverse data sources available by consolidating their data into a single point of access as a foundation for BDA models to generate accurate insights relevant to the organization as a whole, not only to specific processes or sub-functions. Additionally, SCM Big Data sources are frequently created in unstructured formats that are challenging to analyze using conventional IT technologies. While data management has concentrated on increasing the volume and velocity capabilities for transactional data, the number of primary sources of transactional data is still somewhat limited. In SCM data sources, there is an imbalance between the comparatively smaller fluctuations in volume and speed and the bigger differences in data diversity. There is also a positive association between high volume/velocity and unstructured forms. In their conclusion, they made the case that, in order to win with big data, we must no longer view the data as an information asset but rather as a strategic asset. By doing this, businesses involved in SCM could recognize the data's inherent economic value and its potential to be capitalized when used in conjunction with BDA for revenue-generating ventures. Some of the data showed that BDA is still in its early phases in the supply chain, but future steps will showcase its potential through more focused applications in SCM.

Jeihoony et al., 2020 did a study on learning orientation and innovation performance: the mediating influence of operations strategy and supply chain integration. A conceptual framework was created and evaluated utilizing a quantitative and logical methodology by employing structural equation modeling to analyze data collected through survey questionnaires from 243 UK manufacturing companies. Their research demonstrates that while learning orientation affects operations strategy and supply chain integration, it has little immediate effect on innovation performance. Additionally, while cost and delivery strategies have a negligible impact on these variables, quality and flexibility strategies have a beneficial impact on innovation performance and supply chain integration.

CHAPTER THREE

RESEARCH METHODOLOGY AND ORGANIZATIONAL PROFILE

3.1 Introduction

This chapter objectively presents the methodology of the research. The methods projected in this chapter, purpose to accomplish the study objectives and answer the research questions. The methodology chapter commenced by clearly explaining the research design, secondly, research sampling procedures, and then the research instrument. The final stage in this section addresses the explanation of the proposed data analysis.

3.2 Research Design

Research design represents the structure of the research. It serves as a glue that binds all the elements in the study, in order words, it is the plan of the proposed research work (Inaam, 2016). Though there are different forms of research designs, this study employs both descriptive and explanatory research designs. While the descriptive study only observes, explanatory research makes the fan fort to explain the phenomenon. The forces behind the occurrence of the phenomenon are represented by theories or hypotheses. Explanatory research is concerned with cause and effect (Saunders et al., 2007). The main purpose is to explain how one variable affects another variable. Explanatory research holds the assumption that the change in the dependent variable is caused by an external factor. It is usually grounded in theory which helps to answer the how and why questions. In the opinion of Engel and Schutt (2014), explanatory research is the eventual destination of science and on the knowledge continuum, they place it at the apex. Usually, explanatory research is experimental and it allows for the testing of hypotheses (Strydom, 2013). The focus of explanatory research is how or why things occur. Collis and Hussey (2003) believe that explanatory research extends a descriptive study. In this context, the phenomenon observed by descriptive research is explained and analyzed by the researcher to find reasons beyond the description of the characteristics (Blumberg et al., 2005, Collis and Hussey, 2003). In this study, an explanatory approach will be utilized in chapter 4 to test the stated hypothesis. The explanatory approach will be used to test the impact of green warehousing, logistics optimization influences firm performance through supply chain sustainability among manufacturing firms in Ghana. Because this study is predominantly quantitative it employed both descriptive and explanatory approaches. The beginning of the findings presented a description of individual responses. In a nutshell, the basic features of the data gathered will be described to bring out the summaries of the selected sample and measures adopted. The research domain is clarified and the relationships between the variables are established in Chapter four. This approach was found suitable to help test the generated hypotheses for the study. The approach helped to discover the reality and explain what the reality was. It helped to set the conceptual and theoretical framework as well as an explanation of sustainability among pharmaceutical firms in Ghana. Asking the opinion of the respondents in a structured way and analyzing the data using mathematical methods in explaining the phenomena is known as the quantitative approach (Muijs, 2010). This approach provides a detailed explanation for studies that concentrate on examining the relationship between variables (Muijs, 2010).

The survey is one of the methods used in collecting data from a quantitative approach. This method is seen as efficient and very economical in addition, it can capture a great number of respondents (Zikmund et al., 2000). This study used the survey strategy to get the needed information from the target respondents.

3.3 Population of the Study

The relevance of a research population has a great reflection on the quality of the study. Thus, the outcome of the study will be hugely negated if wrong, unqualified, and unsuitable respondents are targeted. Hence, it is all time important to clarify the population and the target population before data is collected. To understand the research population, it is important to differentiate between the target population and the accessible population. While the target population represents the broad group that is of interest to the researcher, the accessible population represents the actual participants that the researcher can include in the study. This is also determined by the unit of analysis, thus if the researcher intends to conduct the study at the organizational level, then it is advisable to use a single response, however, if the study is an individual level. Then the focus could be on multiple respondents from a case study. This study is conducted at the organizational level; hence the target populations include all manufacturing SMEs in Ghana. According to the Registrar's Department of Ghana database, there are about 777 registered manufacturing firms in Ghana (as cited in Agyaben-Mensah et al., 2020). Hence the target population of this study is made up of 777 manufacturing companies in Ghana. Data is gathered from procurement, logistics, and top executives or managers of all the manufacturing companies in Ghana.

3.4 Sample Size and Sampling Technique

In any social science research, the issue of how many respondents should be included in a study or what sample size is adequate remains a puzzle that has received varied opinions. In such regard, varied views have been expressed by different researchers. While a school of thought believes that smaller sample size is well suited for larger populations, other schools believe that it should be representative (Krejcie and Morgan, 1970), relatively homogeneous, or heterogeneous of the population. In the view of Gorsuch (1983) and

Kline (1979), the sample size should be at least 100. Others advise that researchers should get the maximum sample size possible (Rummell, 1970; Humphreys et al., 1969; Guertin and Bailey, 1970; Press, 1972). To avoid all these confusions, Yamane (1967:886) provides a simplified formula to calculate sample sizes. This formula was used to calculate the sample size.

The formula is given us;

$$n=\frac{N}{1:+N(e^2)}$$

Where n is the sample size, N is the population size, and e is the level of precision. When this formula is applied to the above example, we get

$$n=\frac{777}{1:+777(0.05^2)}$$

n=264 firms

Having established the required sample, the method to select these firms is also another issue of concern. The sampling technique can also be used to designate the process of selecting a section from the entire population (Bryman, 2012). Sampling is largely about choosing persons or entities as a subset of a defined population to assess the characteristics of the entire population (Collis and Hussey, 2009). It is very appropriate in a situation where it is not feasible for the researcher to reach the entire population due to challenges such as cost and time constraints (Saunders et al., 2007). Knowing the type of sampling method to apply is important, for it helps the researcher to select the right respondents for the study. It is very suitable in situations where the researcher cannot reach the whole sample or population due to challenges such as time constraints and cost (Saunders et al., 2007). There are two main techniques used in sampling: probability (random) and non-probability. With probability or random sampling, every participant in the population has an equal chance of selection. However, in the instance of non-probability sampling not all the subjects in the population have the chance of being selected (Bhattacherjee, 2012; Kothari, 2004). "Simple random sampling, stratified sampling, systematic sampling, and cluster/area sampling are examples of probability (random) sampling while judgment sampling, quota sampling, and convenience sampling techniques fall under non-probability sampling" (Kothari, 2004, p.15). Considering the possible heterogeneity in the characteristics of the samples that will be drawn from each stratum (Belt/Zone) and to increase precision and to minimize sampling bias, a sample frame will be collected from Ghana Statistical Service to identify the firms in each of the strata and reach out to them through a survey with an online and self-administered questionnaire. Proportionate and adequate sample size will be collected from each category to constitute a total sample size of 200 respondents. The study used stratified random sampling techniques to select target respondents with deep knowledge in lean management and green issues from the target population.

3.5 Data Collection

The two key sources of data for most research is primary and secondary. While primary data consists of first-hand materials that the researcher has gathered himself or herself mainly using questionnaires (Dubey et al., 2016), secondary data in contrast is the information that has been collected by other individual (s) for other purposes (Bryman and Bell, 2007). In this study the main source of data collection is primary. To support or reject the findings from this study, data from secondary sources were reviewed. The primary source of data includes information gathered through questionnaires that were administered to the respondents sampled from pharmaceutical firms in Ghana. In gathering the primary data required in this study, a cross-sectional survey design is utilized. A structured questionnaire with a mainly close-ended format was self-administered to the respondents. The data collection process began with a letter from the University requesting companies to give the researcher permission to collect data of relevance to the study. After the permission letter was taken from the school, the researcher spoke with selected companies to be used in the study. Permission was officially sought from human resource managers, informing them of the purpose of the study and the importance of the data collection for the current study. Those who qualified and were interested in the study were given a statement of consent to read and sign as evidence of their willingness to participate, after which the questionnaires were administered to each respondent. Respondents were given a week to fill the questionnaires and subsequently retrieved from the respondents. Participants who needed clarification on the questionnaire were provided with further clarification to assist them in filling it out.

The questionnaire was the main instrument used to collect primary data. A well-structured questionnaire containing measurement items validated in previous studies will be employed in the study. Each of the variables was measured based on a five (5) point Likert which ranged from 1 (strongly disagree) to 5 (strongly agree). The questionnaire will be structured to reflect the relevant objectives of the research. The questionnaire helped to solicit responses to test all the key variables in the conceptual framework of the study. Using a Five-point Likert scale point (1= “Strongly Disagree” to 5= “Strongly Agree”), each item was measured. The preliminary part consisted of demographic measures which included gender, educational background, work experience, and position within the firm of the participants, of the categorization questions included in the survey, captured the kind of company. The constructs and their respective measures are shown below. Big Data Analytics Capability (BDAC) was measured using five (5) items adopted from (Akter et al., 2016; Srinivasan and Swink, 2017). Items as used are shown below.

BDAC1	We use advanced tools (like optimization/regression/ simulation) for data analysis
BDAC2	We use data gathered from multiple sources (like company reports, tweets, Instagram, YouTube) for data analysis
BDAC3	We use data visualization techniques to assist decision makers in understanding complex information extracted from large data
BDAC4	Our dashboards display information, which is useful for carrying out necessary diagnosis
BDAC5	We have connected dashboard applications or information with the manager's communication devices

Learning Orientation was measured using seven (7) items adopted from (Kumar et al., 2020). Items as used are shown below.

Item	**Learning Orientation**
LO1	Our managers basically agree that their organization's ability to learn is the key to get competitive advantage
LO2	The sense around here is that employee learning is an investment not an expense
LO3	Learning in our organization is seen as a key commodity necessary to guarantee organizational survival
LO4	The basic values of this organization include learning as key to improvement
LO5	There is a good deal of organizational conversation that keeps alive the lessons learned from history
LO6	We always analyze unsuccessful organizational endeavors and communicate the lessons learned widely
LO7	We have specific mechanisms for sharing lessons learned in organizational activities from department to department (unit to unit,

Supply Chain Innovation was measured using seven (7) items adopted from (Panayides and Lun, 2009). Items as used are shown below.

Item	**Statement**
SCIN1	We frequently try out new ideas in the supply chain context.
SCIN2	We seek out new ways to do things in our supply chain
SCIN3	We are creative in the methods of operation in the supply chain.
SCIN4	We often introduce new ways of servicing the supply chain
SCIN5	We motivate supply chain members to suggest new ideas
SCIN6	We pursue continuous innovation in core processes
SCIN7	We pursue new technological innovation

A pilot study is the first step of the entire research protocol and is often a smaller-sized study assisting in planning and modification of the main study (Thabane et al 2010). In this regard a pilot study was carried out using the sample size of 30 respondents from the sample frame. Some of the items including the wording of questions were modified based on the feedback from the pilot study. The Cronbach alpha coefficient for reliability test of the pilot study is as follows: BDAC = 0.78, KC = 0.81 and SCI = 0.71.

3.6 Data Processing and Analysis

Data analysis is the process of using a systematic procedure to draw inferences from data gathered from the field as well as considering the various procedures that can be used to analyze the data (Churchill and Iacobucci, 2009). The researchers further suggest that the research design, kind of data and assumptions made in the research, and concerns associated with the study will influence the suitability of a given technique. Data analysis may follow the quantitative or qualitative procedures in scrutinizing the large volume of information obtained from the field. In the quantitative context, the procedure includes the use of statistical techniques to describe and examine variation in the quantitative measures. The quantitative approach emphasizes the use of either inferential or descriptive statistics (statistical techniques), to understand and establish relationships between constructs.

In this study Statistical Package for Social Sciences (SPSS) version 23 and SmartPLS 3 software will be utilized to conduct descriptive statistics and inferential statistics respectively. The data collected will be coded, cleaned, and prepared for analysis. The data will first be coded in Microsoft excel. In excel the data will be thoroughly checked to avoid possible data entry errors. After cleaning the data will then be exported to SPSS. The data checks in SPSS include missing values, reliability, descriptive statistics, and test of assumptions for multivariate analysis. Subsequently, SmartPLS version 3 (Ringle et al., 2015) will be employed to conduct inferential statistics through multivariate data analysis.

3.7 Reliability and Validity

Evaluating the measurement model is very important in quantitative research, it confirms the validation and the result of the research. It is however important for researchers to concentrate on improving the quality of their work (Heale and Twycross, 2015). Again, there are two vital features to deal with in assessing the measurement model, they include the reliability and validity of the study instrument to be used (Saunders, Lewis, and Thornhill, 2016). Khalid et al. (2012), defined reliability measurement as the degree to which the measurement is free from random error by giving a consistent result. Concurrently, it is known as internal consistency of measurement which mirrors the same underlying construct (Cooper and Schindler, 2003). To test for how reliable an instrument is, Hair et al. (2012), came up with two tests of reliability and they are internal consistency and indicator of reliability. For internal consistency reliability, the researcher used Cronbach Alpha. According to Hair, Sarstedt, Ringle, and Mena (2012), the indicator reliability is used to measure the indicator's variance to explain the latent construct where every indicator's absolute standardized loading should be more than 0.7 (Hair, Ringle, and Sarstedt, 2011). The researchers claim that the indicator loading, between 0.4 to 0.7 should be removed from the scale if deleting the said indicator will increase the composite reliability above the accepted threshold value. However, if the indicator loading is equal to or less than 0.7, it should be removed at all times from the reflective scale. Zikmund (2000), defined validity to be the accuracy of the measurement device and denotes the ability of a scale to measure what is proposed to measure. For quantitative research, the researcher has to certify that the three traditional forms of validity exist in the measurement device and they include face validity, content validity, and construct validity (Heale and Twycross, 2015).

Content Validity: The common method among others is content validity however, it is very needful to be conducted. It tests whether the items would measure all the content which is made to measure in the study (Creswell, 2009; Heale and Twycross, 2015). The content validity is mostly done through reviewing related literature, in this research, the instruments used were validated from past studies. Yet to make sure that it captures all the content of the research, the researcher explored face validity by involving experts to evaluate to ensure that the instruments are suitable in terms of their relevance, appearance, and properly representing the elements (Richard G. Netemeyer, William O. Bearden, 2003).

3.8 Ethical Considerations

Ethics are the moral standards a person must adhere to regardless of place or time (Akaranga and Makau, 2016). Research ethics center on the moral ideals that researchers in their particular fields of study must uphold (Fouka and Mantzorou, 2011). A permission form was provided to the authorities of all selected companies in order to advise them of the potential benefits and dangers of participation and to seek their approval for inclusion in the study. Select businesses were permitted to decline participation in the study. On the consent form, the researcher indicated that all types of anonymity and confidentiality would be observed. Also observed was the right of businesses to determine the time, scope, and conditions of information exchange. In their interactions with subjects, the researcher refrained from engaging in any deceptive practices. In addition, the researcher avoided all sorts of plagiarism and data manipulation.

3.9 Organizational Profile

Given that developed as well as developing nations manufacturing sector accounts for the largest share of the industrial sector (Haraguchi, Cheng, and Smeets, 2017). The manufacturing industries refer to those industries which involve the manufacture and processing of articles and indulge in either creating new commodities or adding value (Pfeiffer, 2017). Dangelico and Vocalelli (2017) describe the term as a manufacturing and marketing segment focused on the manufacture, processing, or preparation of raw material and commodity products, the finished products could be used both as a finished good of production or for sale to customers (Xu, Serrano, and Lin, 2017). Whereas, as per Hitomi (2017), a manufacturing sector could be seen as an economic activity wherein, on a large scale, the material is converted into finished products (Kayanula and Quartey 2000). Added to that, the National Manufacturing Association (USA) proposed the term as the firms engaged in manufacturing and processing of products.

In its industry report, the Ghana Statistical Service (GSS) proposed the term as a collection of activities associated with with goods and services. The Ghana Enterprise Development Commission (GEDC) has described the manufacturing sector in aspects of their machinery and plants. However, Kayanula and Quartey (2000) brought up the underlying potential risk of prioritizing a fixed asset and the potential impact of inflation on valuation, in specific by adopting criteria for fixed assets. The indigenous manufacturing industry supports local businesses and employs a major section of the increasing workforce. Manufacturing, food processing, construction, a small glass industry, textiles and clothing, chemicals and pharmaceuticals, metal processing, furniture and wood products, and leather and footwear are among Ghana's most important manufacturing industries (Addo, 2017).

Among the issues that have plagued this industry is that most manufacturers have not kept up with technological advancements and have failed to invest in new and modernized equipment, resulting in higher electricity usage (Abor and Quartey, 2010). Inadequacies in terms of innovation, knowledge inadequacies, financial constraints and the quality of locally produced items, as well as operational inefficiencies, and insufficient knowledge are just a few of the identified constraints faced by small and medium scale enterprises (Abor, 2015; Oppong et al., 2014; Quartey et al., 2017; Sitharam and Hoque, 2016).

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.1 Introduction

The fourth Chapter presents the analysis and discussions of the findings. The Chapter has five main headings. The first section presents the exploratory data analysis, followed demographic analysis. The second section included descriptive and correlational analyses. The Confirmatory Factor Analysis and model fit index are presented in the third section. The structural model that evaluates the study's hypotheses is evaluated in the fourth section and the discussions on the firth section.

4.2 Exploratory Factor Analysis

Data analysis began with exploratory analysis. Exploratory factor analysis was conducted early on to evaluate data quality. SPSS was used. Subsections examine the response rate, non-response bias, and usual technique bias or variation. Sections 4.1.1, 4.1.2, and 4.1.3 describe the tests and interpretation utilised for this early data quality evaluation.

4.2.1 Response Rate

Most surveys provide the response rate as a percentage. It is derived by dividing the number of surveys distributed by the number of responses. A survey response rate of 50% or above is usually rare. Data was collected from 20 October to 22 December 2022. From the study, 264 were administered to account for non-responses. After analysing the questionnaires for acceptability, 264 were found useful, producing a 100% response rate, which is sufficient for analysis, according to past research (Sun et al., 2022; López, 2022; Lavidas, et al., 2022).

Table 4.1: Responses Rate

Distributed	Collected	Percentage of Usable
Response	264	100%
Non-Response	0	0%
Total	**264**	**100%**

4.2.2 Test for Common Method Bias and Sampling Adequacy

Testing for CMB is important in survey research because difficulties with CMB may affect or distort the results of the relationship between the predictors and dependent variable owing to dependence on a single respondent (Podsakoff and Organ, 1986; Bahrami et al., 2022). Consequently, wrong assumptions are drawn. According to Podsakoff et al. (2003), CMB developed out of the idea of regularity or social acceptability. Any data may be affected by CMB, but there are several ways to lessen its impact. Exploratory Factor analysis showed that Harman's proposed one-factor explanation accounted for variance below the 50% threshold, lending credence to the strategy. Collinearity tests revealed that the VIF statics for all the structures were below Kock's (2015) permissible range (<3.3). Data used in this inquiry did not exhibit any signs of bias due to the commonly used research methodology. By employing principal component analysis, it was shown that the variables were responsible for 47% of the overall variation.

Table 4.2: Test for Common Method Variance (CMV)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	VIF
1	8.851	46.582	46.582	8.851	46.582	46.582	1.964
2	2.118	11.147	57.729	2.118	11.147	57.729	2.272
3	1.602	8.432	66.161	1.602	8.432	66.161	1.913
4	0.955	5.025	71.186				2.324
5	0.834	4.391	75.577				2.226
6	0.581	3.059	78.636				2.235
7	0.508	2.676	81.311				2.394
8	0.495	2.604	83.915				3.104
9	0.446	2.349	86.264				2.612
10	0.393	2.069	88.333				2.583
11	0.349	1.836	90.169				3.078
12	0.326	1.717	91.886				2.746
13	0.309	1.625	93.512				2.720
14	0.252	1.329	94.84				2.014
15	0.239	1.257	96.097				2.596
16	0.222	1.169	97.266				2.632
17	0.193	1.017	98.284				2.607
18	0.172	0.903	99.187				1.683
19	0.155	0.813	100				
Extraction Method: Principal Component Analysis.							

Additionally, the Kaiser-Meyer-Olkin (KMO) and Bartlett sphericity tests were used to evaluate the accuracy of the samples. According to the findings shown in Table 4.3, the Kaiser-Meyer-Olkin level of sampling accuracy is 92.6%, and the results of the Bartlett's test suggest statistical significance (2 = 3434.221, df: 171, Sig.= 0.000). This gives evidence of proper sampling.

Table 4.3: Bartlett's Test of Sphericity and KMO test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.926
Bartlett's Test of Sphericity	Approx. Chi-Square	3434.221
	df	171
	Sig.	0.000

4.2.3 Non-response Bias

Non-response bias was investigated. Non-response bias occurs when a survey has fewer responders than the population. Low survey response rates induce non-response bias, which may undermine sample reliability and study generalizability. In this study, early and late responders were compared to reduce non-response bias. Early responders submitted their questionnaires before the first month, whereas late responders did so later. Oppenheim (2001) suggested that the two groups shouldn't modify any model input variables. This demonstrates that non-response bias is not a concern and that the samples accurately represent the population. The first 132 answers were early and the following 132 late. T-tests checked for non-response bias. The t-test showed no difference (see Table 4.4). The study shows that construct data from the first and last months are identical.

Table 4.4: Results of Independent-Samples t-Test for Non-Response Bias

			Levene's Test for Equality of Variances		
	Group	**Mean**	**F**	**Sig.**	**t**
BDAC	1	20.37	0.404	0.526	3.595
	2	18.87			3.595
OL	1	27.52	0.872	0.351	1.309
	2	26.7			1.309
SCIN	1	28.55	0.005	0.942	2.858
	2	26.98			2.858

4.3 Demographic Information

The demographics of the respondents are included in this section to present information on the subject individuals and the firms that participated in the research. The key data taken from the respondent are gender, age, educational background, department of respondents, position of respondents, age of firms, number of employees, and type of ownership. Out of the 264 responses that were valid, 26.9% were females and 73.1 were males. This data shows that more males than females took part in the study. 3.8% were between 18 and 30 years old, 53.8% were between 31 and 40 years old, 31.1% were between 41 and 50 years old, and 11.4% were over 50 years old. The results show that most of the people who answered were between 31 and 40 years old. 37.9% had a bachelor's degree, 8.3% had a diploma, and 53.8% had done graduate studies (Master's or Ph.D.). The results show that most of the people who answered had a Master's or Ph.D. 54.2 percent of the 264 people who answered were business owners, 29.2% were business owners and managers, 15.5% were managers, and 1.1% said they were production managers.

Most of the people who answered were business owners, according to the results. 18.2 percent of the 264 logistics service companies have been in business for 1 to 5 years, 31.8 percent have been in business for 11 to 15 years, 8.3 percent have been in business for more than 16 years, and 41.7 percent have been in business for 6 to 10 years. The results show that most of the companies that responded have been around for between 6 and 10 years. 40.2 percent of the 264 logistics service companies had between 30 and 99 employees, 3.4% had between 5 and 29 employees, and 56.4 percent had more than 100 employees. The results show that most of the companies that replied had more than 100 employees. 84.1% said the business was owned entirely by Ghanaians, 11.0% said it was owned entirely by foreigners, and 4.9% said it was owned by both Ghanaians and foreigners. The result shows that most of the firms owned by respondents were fully local.

Table 4.5: Demographic Information

Variables	Categories	Frequency	Percent
Gender	Female	58	42.0
	Male	80	58.0
Age	18-30 years	25	18.1
	31-40 years	66	47.8
	41-50 years	36	26.1
	Above 50 years	11	8.0
Level of Education	Bachelor Degree	74	53.6
	Diploma	18	13.0
	Graduate Studies (Master / Ph.D.)	46	33.3
Your Position in the Firm	Business Owner	38	27.5
	Business Owner & Manager	54	39.1
	Manager	32	23.2
	Production Manager	14	10.1
How many years have your firm been in operation?	1 - 5 years	31	22.5
	11 – 15 years	41	29.7
	16 years and above	14	10.1
	6 - 10 years	52	37.7
	Total	**138**	**100.0**

Source: Field Data, 2023

4.4 Correlation Analysis

The correlation coefficients between BDAC and SCI ($r = 0.794$, $P < 0.05$), GC and LO ($r = 0.633$, $P < 0.05$), and LO and SCI ($r = 0.642$, $P < 0.05$) are all very high in Table 4.6. A correlation value of 0–0.30 indicates a weak link, 0.30–0.70 a moderate correlation, and 0.70–1.0 a strong correlation. The variables are strongly correlated.

Table 4.6: Descriptive and Correlation Analysis

Construct	1	2	3
Big Data Analytics Capability	1.000		
Learning Orientation	0.794	1.000	
Supply Chain Innovation	0.633	0.642	1.000

4.5 Confirmatory Factor Analysis

Validating research models is crucial. This study relied on the Cronbach alpha and Composite reliability tests to evaluate the model's structure. The model's reliability was assessed using AVE, Fornell and Larcker, HTMT, and indicator loadings. Cronbach alpha and composite reliability indices examined constructs' internal consistency at 0.7. As demonstrated in Table 4.6, Cronbach's alpha and the composite reliability index above the threshold (Hair et al., 2016). The measuring model's items are supported by this result.

Except for OL7, which had a low indicator loading and was eliminated, all indicators loadings were over 0.7. Convergent validity exists. To demonstrate convergent validity, AVE values were more than 0.5. (See Table 4.7).

Table 4.7: Confirmatory Factor Analysis

Construct	Code	Loadings	CA	CR	AVE
Big Data Analytics Capability	BDAC1	0.781	0.884	0.894	0.681
	BDAC2	0.832			
	BDAC3	0.823			
	BDAC4	0.848			
	BDAC5	0.843			
Learning Orientation	LO1	0.803	0.937	0.940	0.761
	LO2	0.882			
	LO3	0.877			
	LO4	0.887			
	LO5	0.900			
	LO6	0.882			
Supply Chain Innovation	SCIN1	0.816	0.900	0.901	0.627
	SCI2	0.804			
	SCI3	0.764			
	SCI4	0.813			
	SCI5	0.810			
	SCI6	0.799			
	SCI7	0.734			

The Fornell and Larcker technique compared the square root of a construct's average correlation with its strongest link to other constructs (Fornell and Larcker, 1981). As Farrell (2010) proposed, indicators' outer loadings were compared to their cross-loadings with other structures. Henseler et al. (2015) calculated the heterotrait-monotrait (HTMT) ratio of the associations. The evidence suggested an HTMT of less than one (ideally 0.85) (see Table 4.8).

Table 4.8: Heterotrait-monotrait ratio (HTMT)

Construct	Big Data Analytics Capability	Learning Orientation	Supply Chain Innovation
Big Data Analytics Capability			
Learning Orientation	0.518		
Supply Chain Innovation	0.561	0.723	

4.5.1 Model fitness indices

Fitness of Extracted-Index, SRMR, Root Mean Square of Approximation, and Chi-Square are all within their ranges and limits (Table 4.9). Both the uncommon and extracted indices are below 0.9, much below the acceptable criterion. The root shows that the residual is unacceptable since it is the square of the residual and the common root is not near zero. Total Residual Value and Root Mean Square of Approximation are unsatisfactory. Both figures exceed 0.1 and 3. Thus, future study should consider all important constructs. Table 4.9 shows an SRMR of 0.059, which is acceptable for this study. Normed fit index was 0.866 and Chi-square 466.946.

Table 4.9: Model fitness indices

	Saturated model	Estimated model
SRMR	0.059	0.059
d_ULS	0.591	0.591
d_G	0.296	0.296
Chi-square	466.946	466.946
NFI	0.866	0.866

4.5.2 Coefficients of Determination (R2) and Adjusted R2 (R2adj)

Coefficient of determination tests indicate that independent variables explain some of the dependent variable's variation (R2). (R2) assesses how well independent variables predicted the outcome. Falk and Miller (1992) suggested that an R2 of 0.10 or above indicated predictive significance. Table 4.10 shows predictive accuracy (adjusted R2) of 0.228 for Learning Orientation and 0.489 for SC Innovation.

Table 4.10: Coefficients of Determination (R2) and R2Adjusted

Construct	R-square	R-square adjusted
Learning Orientation	0.231	0.228
Supply Chain Innovation	0.492	0.489

4.5.4 The Effect of Prediction Size (Q^2)

Another technique to test a PLS model's correctness is to compute Q2 (Hair et al., 2020). Blindly eliminating a point from the data matrix, allocating missing points, and calculating model phase form this measure (Zhang, 2022). Thus, Q2 combines model explanatory power with sample prediction data (Hair et al., 2020). The blindfold approach uses this approximation to understand output data. Better Q2 values imply higher accuracy when anticipated values are close to baseline (Zhang, 2022). Q2 for an endogenous should be larger than zero to verify the design estimate's correctness. The PLS path model's predictive values are small, medium, and small when Q2 is above 0, 0.25, and 0.50 (Zhang, 2022). Q2 values were 0.207 for learning orientation and 0.241 for SC innovation (see Table 4.11). Thus, all Q-square values were above the threshold, suggesting a strong fit of data and predictive value of the model.

Table 4.11: The Predictive Power of the PLs Model

Construct	Q^2predict
Learning Orientation	0.207
Supply Chain Innovation	0.241

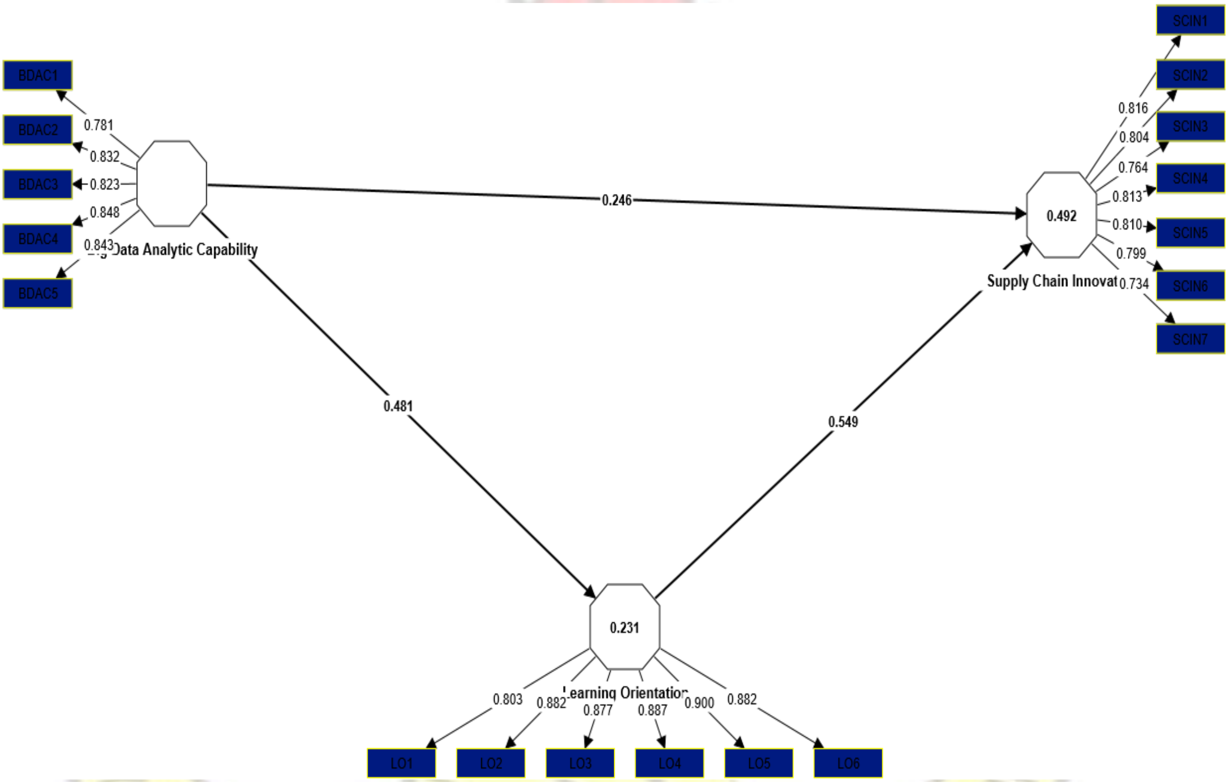

Figure 4.1: Measurement Model Assessment

4.6 Descriptive and Correlation Analysis

The statistical mean's fit to observed data is measured by the mean and standard deviation (Field, 2009). Descriptive analysis results are in Table 4.11. BDAC's mean and standard deviation were (M=3.92; Std. =0.839). SCI scored (M=3.97; Std. =0.819) and LO scored

(M=3.87; Std. =0.965). The result demonstrates that the deviations from the mean values of all constructs were negligible, suggesting that the statistical or computed mean did not differ from the observed mean.

Table 4.12 shows a strong positive connection between BDAC and LO ($r=0.481$, $P<0.05$), BDAC and SCI ($r=0.510$, $P<0.05$), and LO and SCI ($r=0.668$, $P<0.05$). Additionally, correlation values between 0 and 0.30 suggest a weak link, 0.30 to 0.70 a moderate correlation, and 0.70 to 1.0 a significant correlation. This suggests a moderate association between variables.

Table 4.12: Descriptive and Correlation Analysis

Construct	Mean	Std. Dev	1	2	3
Big Data Analytics Capability	3.92	0.839	1.000		
Learning Orientation	3.87	0.965	0.481	1.000	
Supply Chain Innovation	3.97	0.819	0.510	0.668	1.000

4.7 Hypotheses for Direct and Indirect Relationship

The research hypotheses are tested using SmartPLS 4. Results are in Table 4.13. The research mediating and moderating models will be analysed using bootstrapping 5000 times with replacement and standard error estimated according to the measurement model's confidence level (Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). The research examines how learning orientation (LO) mediates big data analytics capabilities (BDAC) on supply chain innovation (SCI).

Table 4.13: Hypotheses for Direct and Indirect Relationship

Path	Path Coefficient	T statistics (|O/STDEV|)	P values	Hypothesis Validation
Big Data Analytics Capability -> Learning Orientation	0.481	6.366	0.000	Accepted
Big Data Analytics Capability -> Supply Chain Innovation	0.246	3.812	0.000	Accepted
Learning Orientation -> Supply Chain Innovation	0.549	9.050	0.000	Accepted
Big Data Analytics Capability -> Learning Orientation -> Supply Chain Innovation	0.264	5.113	0.000	Accepted

Table 4.14 shows that BDAC directly affects LO with B=0.481, t=6.366, P=0.000, and Sig<0.05. Since the p-value for H1 was less than 0.05 and the path coefficient was positive, BDAC had a significant positive direct influence on LO. BDAC improves LO when the path coefficient is positive. Thus, BDAC boosts LO by 48.1%.

BDAC directly affects SCI (B=0.246; t=3.812; P=0.000; Sig<0.05). The path coefficient was positive and the p-value for H2 was less than 0.05, indicating a significant positive direct influence on BDAC to SCI. BDAC enhances SCI because the path coefficient is positive. BDAC accounts for 24.6% of SCI.

LO directly affected SCI (B=0.549; t=9.050; P=0.000; Sig<0.05). Since the p-value was less than 0.05 and the path coefficient was positive, LO had a significant direct influence on SCI, validating the third hypothesis (H3). The positive path coefficient indicates that SCI will improve with LO. LO boosts SCI by 54.9%.

LO indirectly affected BDAC and SCI (B=0.264; t=5.113; P=0.000; Sig<0.05). LO mediates BDAC and SCI positively since the p value for H4 was less than 0.05 and the path coefficient was positive. The positive path coefficient indicates that LO positively mediates BDAC-SCI interactions. This also means that LO mediates 26.4% of the BDAC-SCI connection.

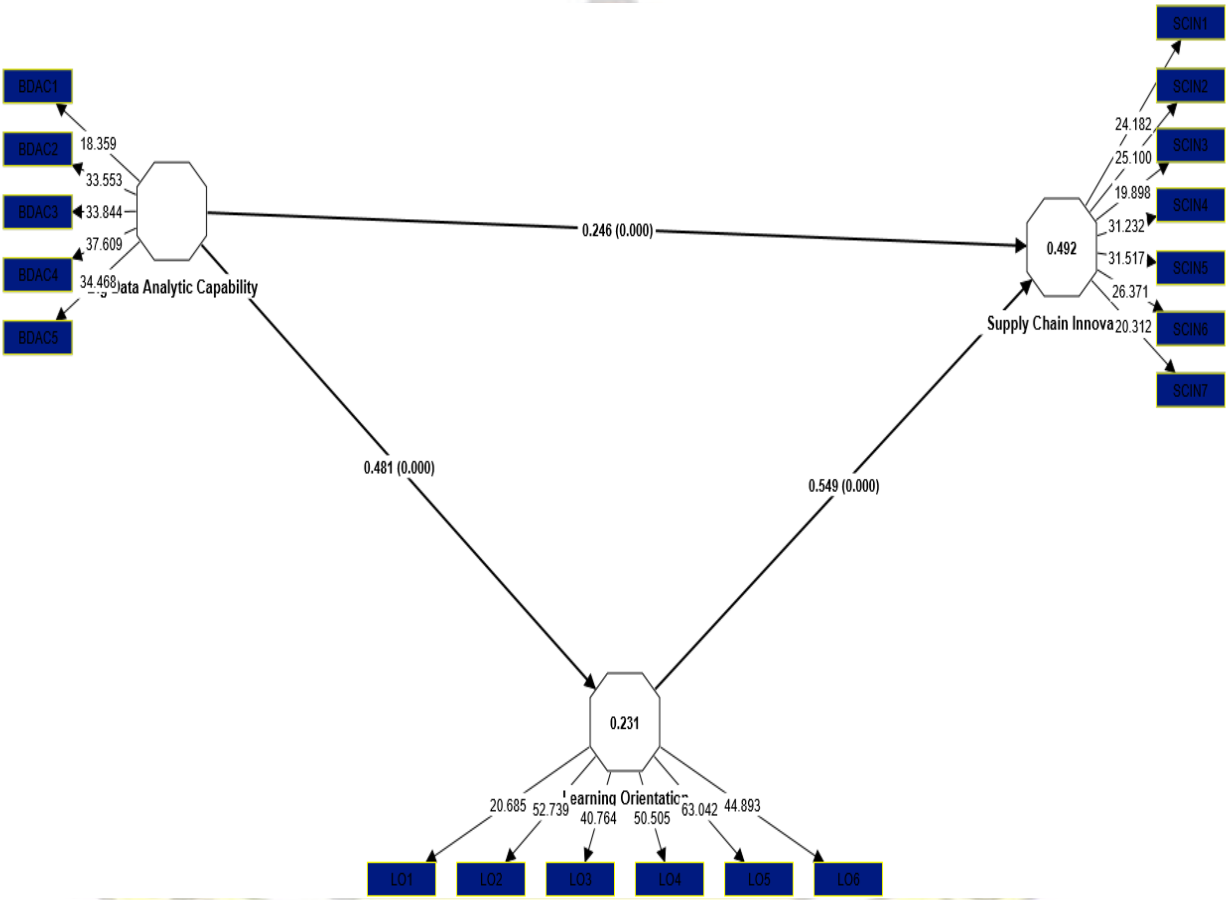

Figure 4.2: Structure Model Evaluation

4.8 Discussion of Results

The results of the study are discussed in light of the previous research in this section. In particular, it discusses how the relationship between big data analytics capabilities (BDAC) and supply chain innovation (SCI) may be explained by the mediating function of a learning orientation (LO). Objectives on the relationship between big data analytics capability (BDAC), supply chain innovation (SCI), and a focus on learning orientation are then investigated further.

4.8.1 Effect of Big Data Analytics Capabilities (BDAC) on Supply Chain Innovation (SCI)

The initial aim of this study determine the effect of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The finding reveals a significant positive direct influence on BDAC to SCI. BDAC enhances SCI because the path coefficient is positive. BDAC accounts for 24.6% of SCI. The findings indicated that SC innovation is enhanced when managers of Ghanaian manufacturing SMEs employ cutting-edge tools (such as optimization / regression / simulation) for data analysis; make use of data from multiple sources (such as company reports, tweets, Instagram, and YouTube); present information useful for diagnosis; and link dashboard applications or information with their communication devices. Results from previous studies are supported by this one. BDAC has been shown to significantly enhance SCI by both Bhatti et al. (2022) and Bahrami et al. (2022) Businesses may be more likely to innovate on a regular basis if their employees are equipped with BDA abilities that allow them to gather environmental data in search of untapped opportunities (Bose, 2009; Chae, 2014; Wang and Dass, 2017; Rialti et al., 2018). Effective BDA features facilitate the evolution of technologies (Mikalef et al., 2020). The importance of BDA resources varies depending on the situation, and some combinations make both incremental and radical process innovation possible (Mikalef and

Krogstie, 2018). Improved capacities for both incremental and radical innovation result from the use of business dynamics analysis (BDA) skills (Mikalef et al., 2019). According to research by Lozada et al. (2019), BDA skills positively influence co-innovation. The BDA helps to stimulate creativity in the service industry's supply chain (Fernando et al., 2018).

4.8.2 Effect of Big Data Analytics Capabilities (BDAC) on Learning Orientation (LO)

The next objective investigates the contribution of big data analytics capabilities (BDAC) on learning orientation (LO) in Ghana. The result shows that BDAC had a significant positive direct influence on LO. BDAC improves LO when the path coefficient is positive. Thus, BDAC boosts LO by 48.1%. The findings indicated that managers from Ghanaian manufacturing SMEs had a more growth-oriented mindset if they used sophisticated data analysis tools (such as optimization/regression/simulation), collected data from a variety of sources (including company reports, tweets, Instagram posts, and YouTube videos), displayed diagnostically relevant data, and synced dashboard applications or data with their communication devices. Consistent with previous research, these results are presented here. According to Jiabin et al. (2021) research, big data analytics skills have an effect on LO. According to research by Watson et al. (2018), the use of BD-driven decision support systems boosts learning orientation by increasing the analytical capabilities and information interchange of organisations. Companies may act as early movers in grabbing attractive innovation possibilities with less uncertainty and risk if they gather up-to-date and real-time information about consumers' profiles, behaviours, and demands as well as rivals' plans and activities (Corte-Real et al., 2017). The research suggests that companies can act as early movers in innovation by leveraging BDAC to gather up-to-date and real-time information about consumers, competitors, and market trends. This strategic use of data reduces uncertainty and risk, providing organizations with a competitive advantage in identifying and seizing innovation opportunities. In summary, the results emphasize the transformative role of Big Data Analytics Capabilities in shaping a learning-oriented mindset within Ghanaian manufacturing SMEs. The findings provide practical insights for businesses seeking to enhance their learning orientation through the strategic adoption of advanced data analytics practices.

4.8.3 Effect of Learning Orientation (LO) on Supply Chain Innovation (SCI)

The third objective investigate the effect of learning orientation (LO) on supply chain innovation (SCI) in Ghana. The result shows that LO had a significant direct influence on SCI, validating the third hypothesis (H3). The positive path coefficient indicates that SCI will improve with LO. LO boosts SCI by 54.9%. According to the findings, learning orientation is enhanced when top management places a premium on research and development, technological leadership, and innovations. This is because it encourages employees at all levels to think outside the box when it comes to the supply chain's day-to-day operations, service delivery, and technology pursuits. This finding is in line with prior research showing that a company's learning orientation is directly associated to its creative activities (Calantone et al., 2002; Rhee et al., 2010; Sheng and Chien, 2016). Investment in education and training (Calantone et al., 2002; Jyoti and Dev, 2015), knowledge creation and application (Baba, 2015), knowledge and information gathering from a variety of sources (Mahmoud and Yusif, 2012), knowledge sharing within the organisation, and openness to new ideas are all examples of learning activities that can flourish in an organisation with a learning orientation. Because of this, the company is able to learn from a variety of external sources, which, when combined with inside expertise, produces novel solutions to problems. In reality, a company's innovation performance may be enhanced by a learning orientation since it encourages competencies including innovation, strategic decision making, and product creation (D'Angelo and Presutti, 2018).

Strategic alignment, which includes technology and new product development-market alignment (Gatignon and Xuereb, 1997; Voss and Voss, 2000), improves throughout this learning process if a business is in sync with its external and internal environment (Mahmoud and Yusif, 2012).

4.8.4 Mediating Role of Learning Orientation (LO)

The last objective of this study determine the mediating effect of learning orientation (LO) of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The finding of this study reveals that LO positively mediates BDAC-SCI interactions. This also means that LO mediates 26.4% of the BDAC-SCI connection. This confirms the findings of earlier investigations. According to Hurley and Hult (1998), a learning orientation is an essential aspect of company success since it makes a significant contribution to strategic marketing. In this regard, Chen et al. (2017) shown that a focus on learning mediates the relationship between an entrepreneur's mindset and the success of their business. The authors of this research suggest that senior management adopt measures to improve the use of BDAC to encourage risk-taking and new venture creation. The inclusion of monetary or non-monetary incentives for workers involved in creative BD-based experimentation and exploration activities, for example, may stimulate internal cooperation on collaborative innovative initiatives based on data that demand the acceptance of high risks and responsibilities. Employees that have a "learning orientation" actively seek out new information and put it to use in order to improve the company's daily operations. Therefore, businesses should invest in their workers' education and foster an environment that rewards original thinking and action

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The main objective of the study is to examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. In the first portion of the chapter, the study's results and conclusion are summarized and briefly addressed. The chapter concludes with suggestions for further study.

5.2 Summary

5.2.1 Effect of Big Data Analytics Capabilities (BDAC) on Supply Chain Innovation (SCI)

The initial aim of this study determine the effect of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The finding reveals a significant positive direct influence on BDAC to SCI. BDAC enhances SCI because the path coefficient is positive. BDAC accounts for 24.6% of SCI. The findings indicated that SC innovation is enhanced when managers of Ghanaian manufacturing SMEs employ cutting-edge tools (such as optimization / regression / simulation) for data analysis; make use of data from multiple sources (such as company reports, tweets, Instagram, and YouTube); present information useful for diagnosis; and link dashboard applications or information with their communication devices.

5.2.2 Effect of Big Data Analytics Capabilities (BDAC) on Learning Orientation (LO)

The next objective investigate the contribution of big data analytics capabilities (BDAC) on learning orientation (LO) in Ghana. The result shows that BDAC had a significant positive direct influence on LO. BDAC improves LO when the path coefficient is positive. Thus, BDAC boosts LO by 48.1%. The findings indicated that managers from Ghanaian manufacturing SMEs had a more growth-oriented mindset if they used sophisticated data analysis tools (such as optimization/regression/simulation), collected data from a variety of sources (including company reports, tweets, Instagram posts, and YouTube videos), displayed diagnostically relevant data, and synced dashboard applications or data with their communication devices.

5.2.3 Effect of Learning Orientation (LO) on Supply Chain Innovation (SCI)

The third objective investigate the effect of learning orientation (LO) on supply chain innovation (SCI) in Ghana. The result shows that LO had a significant direct influence on SCI, validating the third hypothesis (H3). The positive path coefficient indicates that SCI will improve with LO. LO boosts SCI by 54.9%. According to the findings, SC innovation is enhanced when top management places a premium on research and development, technological leadership, and innovations. This is because it encourages employees at all levels to think outside the box when it comes to the supply chain's day-to-day operations, service delivery, and technology pursuits.

5.2.4 Mediating Role of Learning Orientation (LO)

The last objective of this study determine the mediating effect of learning orientation (LO) of big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. The finding of this study reveals that LO positively mediates BDAC-SCI interactions. This also means that LO mediates 26.4% of the BDAC-SCI connection. This research suggest that senior management adopt measures to improve the use of BDAC to encourage risk-taking and new venture creation. The inclusion of monetary or non-monetary incentives for workers involved in creative BD-based experimentation and exploration activities, for example, may stimulate internal cooperation on collaborative innovative initiatives based on data that demand the acceptance of high risks and responsibilities. Employees that have a "learning orientation" actively seek out new information and put it to use in order to improve the company's daily operations. Therefore, businesses should invest in their workers' education and foster an environment that rewards original thinking and action.

5.3 Conclusion

The main objective of the study is to examine the mediating role of learning orientation (LO) on big data analytics capabilities (BDAC) on supply chain innovation (SCI) in Ghana. A descriptive and explanatory research designs was employed for this study's data collection. A quantitative method was used for this investigation. The 264 procurement, logistics, and top executives or managers were chosen using a stratified sampling process. The major method of collecting information was a predetermined questionnaire. Statistical analysis was performed using both SPSS v26 and SmartPls v4. The data was analysed using both descriptive and inferential methods. The finding reveals a significant positive direct influence on BDAC to SCI and LO. BDAC had a significant positive direct influence on LO. Lastly, LO positively mediates BDAC-SCI interactions. When senior management values research and development, technical leadership, and innovations, SC innovation improves. It encourages all workers to think creatively about supply chain operations, service delivery, and technology. The research advocated emphasising staff development and encouraging creative behaviour to attain competitive advantage and company sustainability.

5.4 Recommendations

From the study's results, this section offers advice to different stakeholders. Management and researchers are encouraged to consider these suggestions.

BDAC positively affects SCI directly. SC innovation is enhanced when managers of Ghanaian manufacturing SMEs use cutting-edge tools (such as optimization / regression / simulation) for data analysis; use data from multiple sources (such as company reports, tweets, Instagram, and YouTube); present information useful for diagnosis; and link dashboard applications or information with their communication devices.

BDAC directly affected LO positively. Managers from Ghanaian manufacturing SMEs had a more growth-oriented mindset if they used sophisticated data analysis tools (such as optimization/regression/simulation), collected data from a variety of sources (including company reports, tweets, Instagram posts, and YouTube videos), displayed diagnostically relevant data, and synced dashboard applications or data with their communication devices.

LO directly affected SCI. When senior management values research and development, technical leadership, and innovations, SC innovation improves. It encourages all workers to think creatively about supply chain operations, service delivery, and technology. This research found LO positively mediates BDAC-SCI interactions. The research advocated emphasising staff development and encouraging creative behaviour to attain competitive advantage and company sustainability.

5.5 Implications of findings

5.5.1 Theoretical Implications

The theoretical contribution of the results, framed within the context of Dynamic Capability Theory (DCT), provides insights into how organizations can develop and leverage dynamic capabilities to enhance their competitiveness in the ever-changing business environment. Dynamic Capability Theory, developed by Teece, Pisano, and Shuen, focuses on an organization's ability to integrate, build, and reconfigure internal and external competencies to adapt to a rapidly changing environment. The results contribute to the theoretical understanding of dynamic capabilities by highlighting the role of Big Data Analytics Capability (BDAC) as a foundational element. BDAC is identified as a dynamic capability that enables organizations to adapt and respond to changes in the business environment, fostering a more flexible and innovative supply chain. The identification of Learning Orientation (LO) as a mediator between BDAC and Supply Chain Innovation (SCI) enriches the theoretical framework. According to DCT, learning is a crucial component of dynamic capabilities. The findings suggest that the organization's ability to learn and adapt mediates the relationship between its analytical capabilities (BDAC) and the innovation outcomes in the supply chain. The results provide empirical evidence of dynamic capabilities in action. BDAC is shown not only to directly influence SCI but also to do so indirectly through its impact on the organization's learning orientation. This aligns with the DCT perspective, where dynamic capabilities involve not only possessing certain resources but also the ability to orchestrate and reconfigure them to address changing circumstances. The study integrates well with the Resource-based View (RBV) within the framework of DCT. BDAC can be considered as a valuable and rare resource that contributes to the competitive advantage of organizations. The RBV, coupled with DCT, provides a comprehensive perspective on how firms can leverage their internal resources and capabilities to achieve sustained competitive advantage. The findings support the notion that dynamic capabilities, as highlighted by DCT, enable organizations to adapt to environmental changes. In this case, the utilization of BDAC allows organizations to not only gather and analyze large sets of data but also to dynamically adjust their strategies and operations based on the insights gained, fostering innovation in the supply chain. The identification of learning orientation as a mediating factor underscores the importance of continuous learning as a core capability within the framework of DCT. Organizations need to cultivate an environment where learning is embedded in their culture, processes, and strategies to effectively translate BDAC into innovations within the supply chain. The results contribute to the understanding of how dynamic capabilities, such as BDAC, provide organizations with strategic flexibility and the ability to reconfigure their resources. The ability to adapt and reconfigure resources is essential for organizations to respond proactively to market changes and capitalize on emerging opportunities. In summary, the theoretical contribution of the results within the framework of Dynamic Capability Theory enriches our understanding of how organizations can harness Big Data Analytics Capability, foster a learning-oriented culture, and ultimately drive innovation within their supply chains. These insights provide a valuable foundation for scholars and practitioners interested in understanding and cultivating dynamic capabilities in the contemporary business landscape.

5.5.2 Practical Implications

The practical implications of the results, indicating a significant relationship between Big Data Analytics Capability (BDAC), Learning Orientation (LO), and Supply Chain Innovation (SCI), are noteworthy for organizations seeking to leverage data-driven strategies for improved supply chain performance. Here are practical implications based on the findings: Organizations should consider strategic investments in developing and enhancing their Big Data Analytics Capability. This involves acquiring sophisticated data analysis tools, fostering skills in BDAC among employees, and staying updated on emerging technologies in data analytics. Organizations should actively promote a learning-oriented culture among their employees. This involves encouraging a mindset that values continuous learning and adaptation to changing market conditions. Leadership should prioritize learning initiatives and provide resources for employee development. Managers and decision-makers should integrate learning orientation into various aspects of business practices. This includes decision-making processes, strategy formulation, and day-to-day operations. By embedding a learning mindset, organizations can better adapt to market dynamics and identify opportunities for supply chain innovation. The findings highlight the importance of diverse data collection sources and sophisticated analysis tools. Organizations should focus on expanding their data collection capabilities to include a wide range of relevant sources. Additionally, investing in advanced analytics methodologies will enable more insightful interpretation of the collected data. Organizations should prioritize the integration of real-time information accessibility through tools such as dashboard applications synced with communication devices. This ensures that decision-makers have timely and relevant data at their disposal, facilitating quicker and more informed decisions that contribute to supply chain innovation. Recognizing the mediating role of Learning Orientation between BDAC and Supply Chain Innovation, organizations should specifically focus on fostering a learning-oriented environment. Improvements in BDAC may directly impact LO, which in turn contributes to supply chain innovation. Therefore, efforts to enhance BDAC should be complemented by initiatives to strengthen learning capabilities. Encouraging collaboration between different functional areas within the organization is crucial. Cross-functional collaboration ensures that insights gained from BDAC are effectively translated into actionable strategies for supply chain innovation. This involves breaking down silos and promoting communication and knowledge sharing among departments. The ability to adapt to market changes is a key implication. Organizations should use BDAC and the associated learning orientation to build agility into their supply chain processes. This allows for a more responsive and dynamic approach to changes in customer demands, industry trends, and competitive landscapes. Establishing mechanisms for continuous monitoring and evaluation of the impact of BDAC on learning orientation and, subsequently, on supply chain innovation is essential. This involves setting key performance indicators (KPIs) and regularly assessing progress to ensure that strategies are yielding the desired outcomes. In conclusion, the practical implications emphasize the need for organizations to strategically integrate BDAC, learning orientation, and supply chain innovation into their business practices. By doing so, they can create a more adaptive, informed, and innovative approach to supply chain management in the rapidly evolving business landscape.

5.6 Suggestions for Future Research

First, it is difficult to establish causality when just descriptive and explanatory data are at hand. Future research may be able to empirically analyse the direction of causality using longitudinal and cross-sectional data. Using quantitative methods, the study investigated how learning orientation (LO) influences big data analytics capabilities (BDAC), and how this, in turn, influences supply chain innovation (SCI). As a result, future studies with the same aims may need to rely on qualitative methods. Studying the impact of learning orientation (LO) on big data analytics capabilities (BDAC) and supply chain innovation (SCI) suggests that new statistical analytic methods might be useful in future studies. Future studies might replicate this research in other nations to assess the reliability and applicability of the results. Therefore, future research should go beyond the study's single mediational element, learning orientation, and include additional factors such as market orientation.

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